### Workshop

### **Future Directions in Systems and Control Theory**

Friday , June 25 Viewgraphs - Volume 4

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### Workshop On

### FUTURE DIRECTIONS IN SYSTEMS AND CONTROL THEORY

### NEW PROBLEMS AND METHODS IN THE CONTROL OF PHYSICAL SYSTEMS

Cascais, Portugal June 22-25, 1999

> Roger Brockett June, 1999

### The Outline

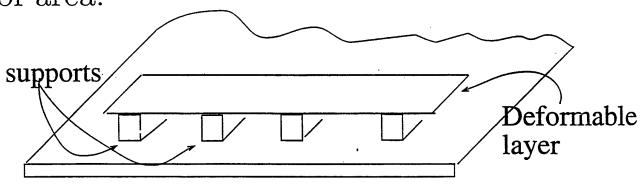
- 1. Elastic Networks (macro-machines)
- 2. Electrostatically Driven Elastic Networks
- 3. Piezoelectrically Driven Elastica
- 4. Actuators
- 5. Models for Hysteresis
- 6. Nonlinear Oscillatory Effects

### Elastic Networks

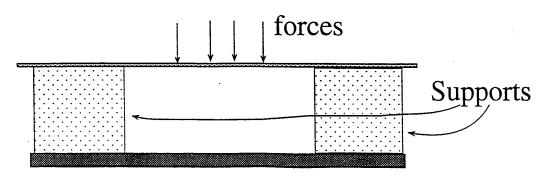
Bending beam equation relates the curvature and the moment

$$\kappa = \frac{M}{EI}$$

E = Young's modulus, I = second moment of area.

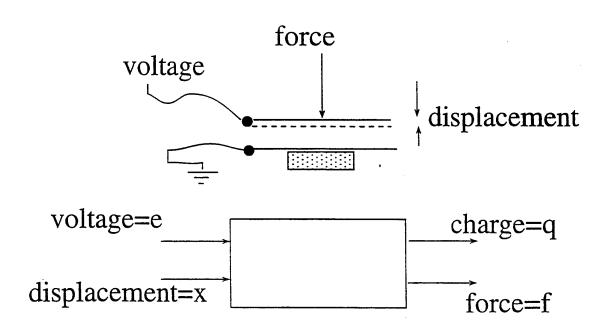


Structures tend to be complex with many loops and few (if any) "pin joints". Flexures are easier to fabricate than bearings. (Later discussion of valves, arrays of mirrors, ...



### Interpreting Some Basic Physics

Stored energy in terms of capacitance and voltage or charge:  $E = \frac{1}{2}Ce^2 = \frac{1}{2C}q^2$   $C = A\epsilon/d$  for parallel plate capacitor.



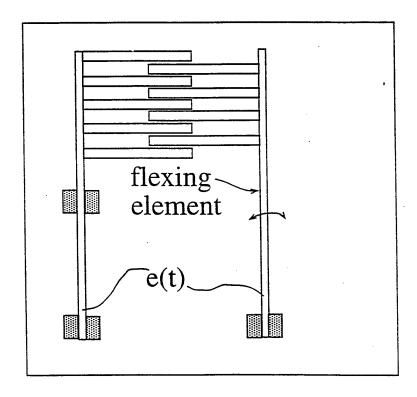
Linearizing about  $(e_0, x_0)$ 

$$\begin{bmatrix} \delta q \\ \delta f \end{bmatrix} = \begin{bmatrix} C(x_0) & \frac{\partial C}{\partial x} e_0 \\ \frac{\partial C}{\partial x} e_0 & \frac{1}{2} \frac{\partial^2 C_0}{\partial x^2} e_0^2 \end{bmatrix} \begin{bmatrix} \delta e \\ \delta x \end{bmatrix}$$

surportance of aff-diagonal terms

### Electrostatic Motors

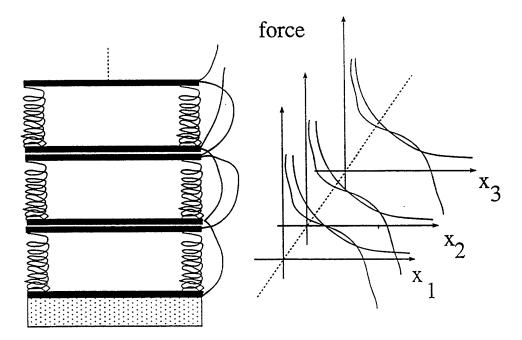
One way in which electrostatic and elastic effects have been combined in devices is in the design of tuning forks. The diagram below illustrates a sample design for an electrically driven vibrating element.



The force on the vibrating element can be determined from the derivative of the capacitance

### Electrostrictive Stacks

Uses high permittivity dielectric thus yielding large values for C and  $\frac{\partial C}{\partial x}$ 

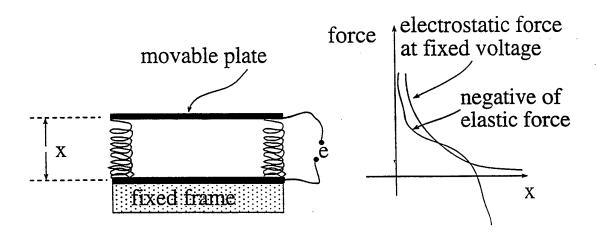


Inserting insulating layers permits the use of lower voltages for reasonable strains.

Illustrating the possibility of multiple equilibria and the basis of hysteresis.

### Electric and Elastic Effects

The plates of the capacitor will be held in position by a system with mechanical compliance.



$$\begin{bmatrix} \delta q \\ \delta f \end{bmatrix} = \begin{bmatrix} C(x_0) & \frac{\partial C}{\partial x} e_0 \\ \frac{\partial C}{\partial x} e_0 & k(x_0) + \frac{1}{2} \frac{\partial^2 C_0}{\partial x^2} e_0^2 \end{bmatrix} \begin{bmatrix} \delta e \\ \delta x \end{bmatrix}$$

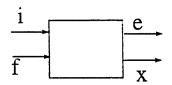
Electrostatic force falls off with increasing x. Note the possibility of multiple equilibria even if the elastic law is linear. Some will be unstable.

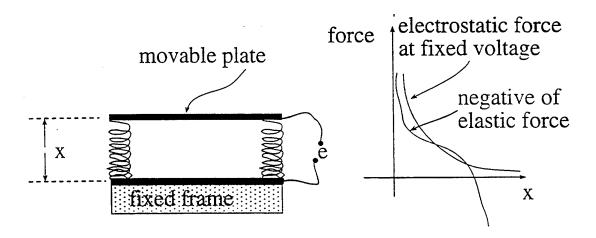
### Introducing Dynamics

Lagrangian depends on electrostatic energy V and elastic energy E  $L(\dot{x},x) = \frac{1}{2}m\dot{x}^2 - \frac{1}{2}C(x)e^2 - E(x)$ 

$$m\ddot{x} + \frac{\partial V}{\partial x} + \frac{\partial E}{\partial x} = f$$

$$\frac{d}{dt}C(x)e = i$$

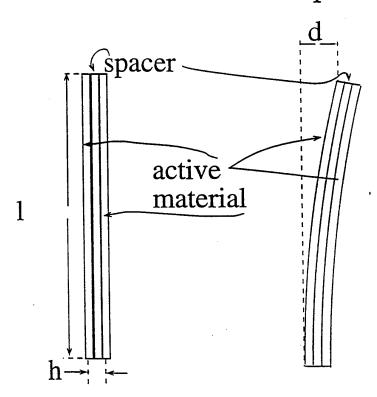




Highly nonlinear—equilibrium comes from electrostatic-elastic balance. Electrical termination helps determine mechanical compliance.

### The Small Strain Problem

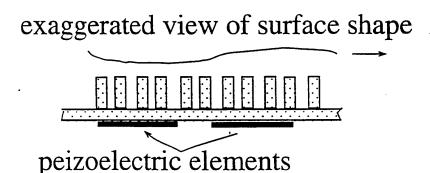
For common piezoelectric materials the strain is small,  $\Delta l/l \approx 10^{-4}$ The effect can be amplified with bilayers



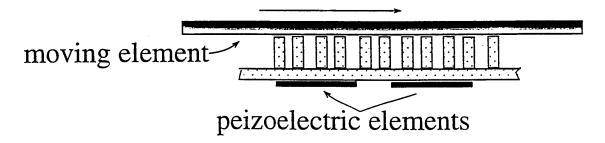
Assume that the layer on the left expands while the layer on the right contracts in equal amount. Then the curvature and displacement are

curvature =  $\frac{2\Delta l}{l \cdot h}$  displacement =  $\frac{l\Delta l}{h}$ 

A correctly phased set of sinusoidal voltage applied to a set of benders produces a change in the geometry of a solid in the form of a traveling wave.



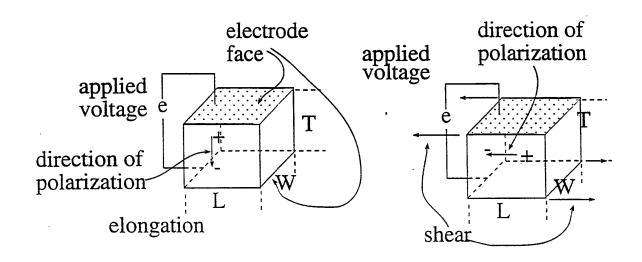
The traveling wave can be coupled to a moving element to produce linear motion.



This is the basis for "ultrasonic" motors.

### Piezoelectric effects (non high frequencies) (x social state unitors)

An applied voltage produces a change in the geometry of a solid. If the solid is a polarized sample of a material such as barium titanate the change is significant.



$$\begin{bmatrix} \frac{\delta L}{L} \\ \frac{\delta W}{W} \\ \frac{\delta T}{T} \end{bmatrix} = \begin{bmatrix} d_{31} \\ d_{31} \\ -d_{33} \end{bmatrix} \stackrel{e}{T} \text{ and } \theta = d_{15} \stackrel{e}{T}$$

 $d_{13}$   $d_{33}$  and  $d_{15}$  are material properties.  $\theta$  is the shear angle in radians

### Poling Piezoelectrics

Many piezoelectric materials acquire their special properties from the presence of internal electric dipoles whose existence is characteristic of ferroelectric materials. Ferroelectric materials, like feromagnetic materials, are most useful when prepared so as to be in particular equilibrium states. In the case of ferroelectrics the preparation process produces an internal polarization and is achieved by application of a strong electric field during manufacture. The effect of an electric field applied subsequently will depend on the orientation of the applied field, relative to the orientation of the polarization.

### Hysteresis and Multiple Equilibria

Hysteresis is essential to the operation of ferromagnetic, ceramic piezoelectrics and phase change materials.

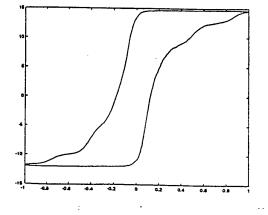
Hysteresis is both a static and a dynamic phenomenon.

A simple dynamic model for hysteresis takes the form

$$\dot{H} = H^2 N(u) - 2HN(u)H + N(u)H^2$$

If H is n by n and symmetric and N is diagonal then the system can have as many as n! equilibrium states. Typically the output variable would take the form

$$y(t) = \text{tr } (H(t)M)$$
  
with  $M$  constant.



### Actuation with Phase Change

Certain materials such as the nickel-titanium alloy Nitinol, change their interna structure at a critical temperature. This phase change is accompanied by a change in the geometry. If the sample is in the form of a wire there may be as much as a 10% change in its length. A prototype temperature-stress-length diagram and block diagram suggestive of the use of heat flow and stress as inputs, is shown.



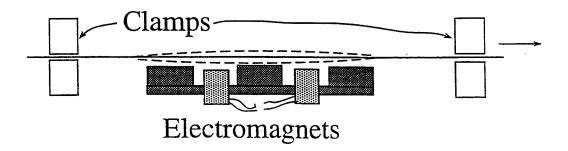
Nitinol has been incorporated in a variety of devices in which the temperature change is produced by an electric current.

### The Concept of Rectification

Small strain, high frequency oscillations must be "rectified" mechanically to generate rectilinear motion. What forms do mechanical rectifiers take?

$$\dot{x} = u$$
 becomes  $\dot{x} = \sin \omega t$   
 $\dot{y} = v$  becomes  $\dot{y} = \cos \omega t$   
 $\dot{z} = xv - yu$  becomes  $\dot{z} = 1$ 

Inchworm kinematics involve clamping and deformation—a "discrete" version of these equations.



### References

- 1. James R. Melcher, Continuum Electromechanics, MIT Press, Cambridge, MA. 1981.
- 2. Piezo Systems Product Catalog, Piezo Systems Inc. Cambridge, MA
- 3. Encyclopedia of Physics, (Rita Lerner and George Tigg, Eds.) VCH Publishers, New York, 1991.
- 4. Richard Feynman, et al. Lectures on Physics, Addison-Wesley, Reading MA, 1963.
- 5. R. W. Brockett, 'On the Rectification of Vibratory Motion," Sensors and Actuators, Vol. 20 (1989) pp. 91-96.

# Hierarchical Hybrid System Design for Unmanned Aerial Vehicles

S. S. Saskry <u>Intelligent Wachines and Robofics Laboratory</u> Department of Riectrical Engineering and Computer Sciences University of California at Berkeley



- Motivation
- System Architecture
  - Hybrid Systems
- Trajectory Generation & Flight Mode Selection
  - Reactive System Synthesis
    - Hybrid Simulation
- Numerical Method for Envelope Protection Controller Synthesis
  - Future Research

### 

- = Design a multi-vehicle multi-modal control system for Unmanned Aerial Vehicle (UAV)
- Intelligent coordination among agents
- Suarantee

  Countier Resolution

  Safety

  Performance

  Figure Researching

  Acti Path Following

  Niccion completion

  Pursuit-Evasion Safety
  - Performance

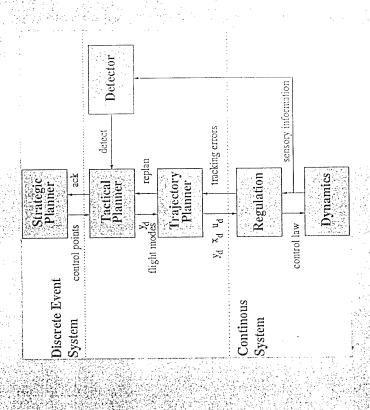


## System Architectus

- Elierarchical Approach

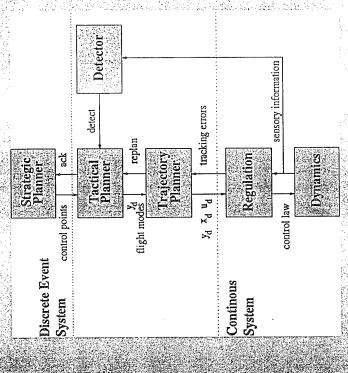
  - ATMS PATH AHS
- ्रह्य 🗸 Communication Networks
- System Architecture
  - FMS

- Strategic PlannerTactical PlannerTrajectory PlannerRegulation
- Detector
- Dynamics



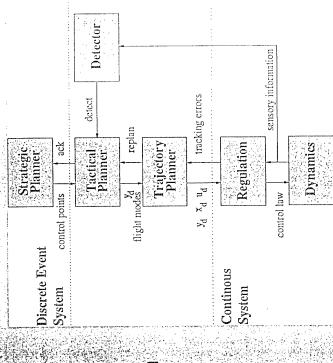
Trajectory as a sequence of way-points

் ©ommunication among UAVs



### 

- Tactical Planner
- ် Coordination among UAVS ိ
  - Conflict resolution
    - Fault handling
- Cutput trajectory generation Flight mode sequence generation
  - Utilizes abstracted (kinematic) model

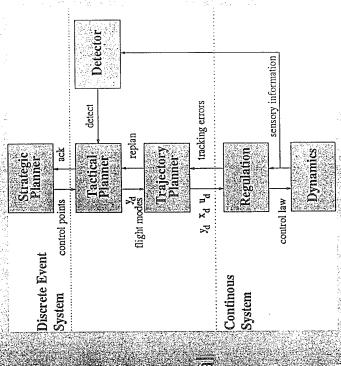


## Sylectical States of the second secon

Defector

Monitors changes in states:

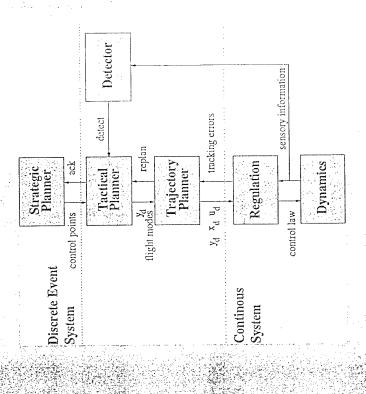
and environments: chiefly
fault modes, conflict
potential, pop-up obstacles
in Limited sensing capability
Planner



## Story Pichies Constants

### FMS

Trajectory Planner
State and input trajectory
generation based on the
given output trajectory and
flight mode
Utilizes dynamical model
Flight Envelope protection

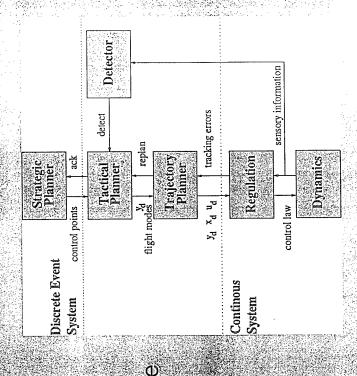


## System Architecture

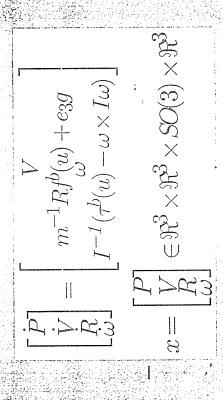
🚡 Regulation

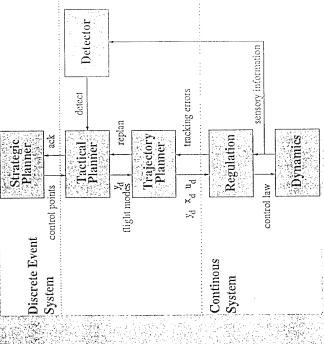
Sontaining sets of flight mode controllers

Controller switching based on the flight mode sequence Utilizing state and input trajectory Tracking error calculation



### Dynamics





## System Architectic

Flight Mode Based Control System Design

Flight Mode

each corresponds to controlling different output variables in represents different control mode of the aerial vehicle and the dynamics.

- Helicopter and Aircraft have four inputs

- A flight mode is constructed by defining four outputs to form a square system from the output set

.. Total 15 combinations

$$y = [p_x \ p_y \ p_z \ \phi \ \theta \ \psi]^T$$

### Lyone System

### Research Issues

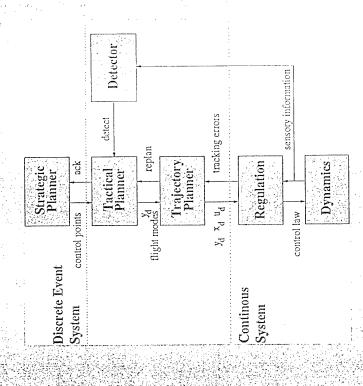
Continuous and discrete state
 spaces

### HWorld System

Multiple, interacting modes of operation

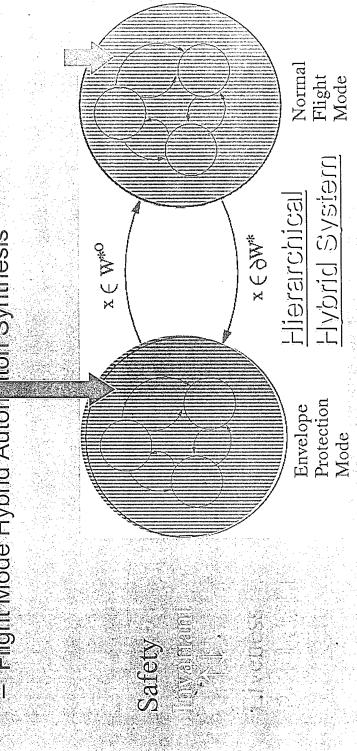
### Safety and Liveness

Hierarchical Hybrid System



Two Major Research Directions

— Numerical Method for Envelope Protecting Controller Synthesis
— Flight Mode Hybrid Auton ton Synthesis



### Majska die

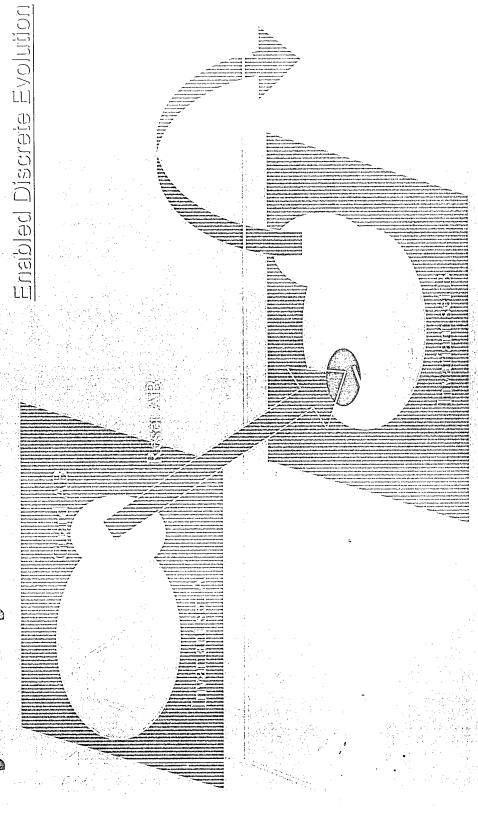
## Hybrid Automata (Lygeros and Sastry, 1999)\*

 $H = (Q, X, V, Y, \mathrm{Init}, f, h, \mathrm{Inv}, E, G, R, \phi)$ 

Q is a finite collection of discrete state variables;
X is a finite collection of continuous state variables;
V is a finite collection of input variables, V = V<sub>D</sub> ∩ V<sub>C</sub>;
Y is a finite collection of output variables, Y = Y<sub>D</sub> ∩ Y<sub>C</sub>;
Init ⊆ Q × X is a set of initial states;
f: Q × X × V → ℝ<sup>n</sup> is a vector field;
h: Q × X × V → ℝ<sup>n</sup> is a vector field;
h: Q × X → Y is an output map;
Inv: Q → 2<sup>X×V</sup> assigns to each q ∈ Q an invariant set;
E ⊂ Q × Q is a collection of discrete transition;
G: E → 2<sup>X×V</sup> assigns to each e ∈ E a guard;
R: E × X × V → 2<sup>X</sup> defines a reset relation; and,
Φ: Q × X → 2<sup>V</sup> defines a set of admissible inputs.

Lipschitz continuous in x and f(q, x, v) is continuous in v. Definition: An execution  $\chi$  of a hybrid automaton  $H \in \mathcal{H}$  is a collection  $\chi = (\tau, q, x, v, y)$  with  $\tau \in \mathcal{T} = \{ [\tau_i, \tau_i'] \}_{i=1}^{\mathcal{N}}$ ,  $q: \tau \to Q, x: \tau \to X, v: \tau \to V$ , and  $y: \tau \to Y$  satisfying: Assumption: Auume f(q, x, v) and h(q, x) are globally

- Initial Condition:  $(q(\tau_0), x(\tau_0)) \in Init;$ Continuous Evolution: for all i with  $\tau_i < \tau'_i$ , q, x, v, y are continuous over  $[\tau_i, \tau'_i]$  and
- $\forall t \in [\tau_{i}, \tau_{i}'), (x(t), v(t)) \in \text{Inv}(q(\vec{t})) \text{ and } \dot{x} = f(q(t), x(t), v(t)); \\ \dot{D}iscrete Evolution: \forall i, 1) \ (q(\tau_{i}'), x(\tau_{i}')) = (q(\tau_{i+1}), x(\tau_{i+1})); \\ \dot{2}) \ e_{i} = (q(\tau_{i}'), q(\tau_{i+1})) \in E, \ (x(\tau_{i}'), v(\tau_{i}')) \in G(e_{i}), \\ and \ x(\tau_{i+1}) \in R(e_{i}, x(\tau_{i}'), v(\tau_{i}'));$
- Input Evolution:  $\forall t \in \tau$ ,  $v(t) = \phi(q(t), x(t))$ ; Output Evolution:  $\forall t \in \tau$ , y(t) = h(q(t), x(t)).



## ð

## Tajectory Generation and Flight Mode Selection

- Output path planning and flight mode scheduling (Egerstedt, Koo, Hoffmann & Sastry, HSCC, 1999)
- Generation flat output trajectories and flight mode sequence associated
- Each closed loop flight mode dynamics modeled by linear system and boundary conditions
- Mode switching occurs at specific time

$$\dot{x} = A_i x + b_i u$$
,  $x \in \mathbb{R}^n$ ,  $u \in \mathbb{R}$ ,  $i = 1, ..., N$ 

## Trajectory Generation and Flight Mode Selection

S. Quitput path planning and flight mode scheduling

Convex optimization problem

Computationally efficient optimal trajectory generation

Optimal flight mode sequence synthesis

- Weighting matrix specifies how important to have the state being close to the desired one at a specific time

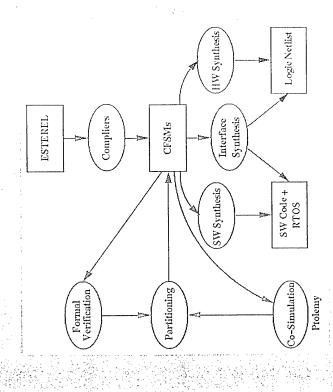
$$J(u) = \frac{1}{2} \rho \int_0^T u(s)^2 ds + \sum_{k=1}^m \frac{1}{2} (x(t_k) - \alpha_k)^T \tau_k(x(t_k) - \alpha_k)$$

# Reactive System Synthesis

# System Specifications Reactivity Concurrency/Sequencing Strict time and reliability Deterministic

### POLIS

- Design prototyping
  - Ptolemy Validation



# Reactive System Synthesis

or Reactive System Design

- Esterel: Synchronous Language

Signal reading/writing

Basic control and looping Sequencing

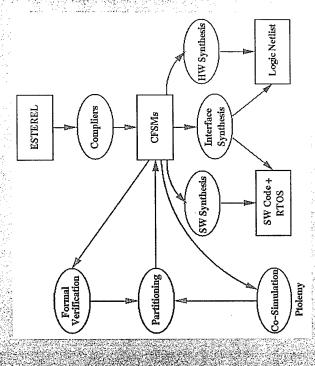
Concurrency Preemption

- Real-time system synthesis

: S.HW//SW partition

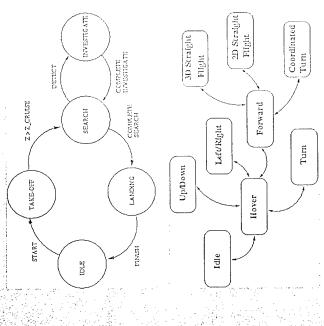
--- Verification

ি ু Finite State Machine (FSM)

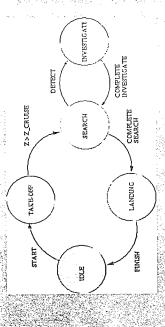


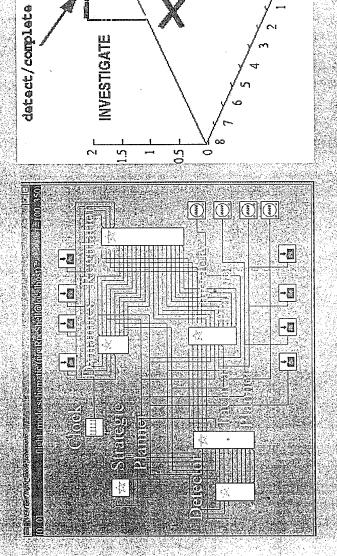
# Reactive System Synthesis

- Reactive System Design
- Tactical Planner
- Operation mode switching
  - Flight mode switching
    - Trajectory Planner
- Trajectory generation
  - Dynamics
- Time Discretization of



# Seactive System





SEARCH

Hierarchical Hybrid System Simulation(Liu, Liu, Koo, Sinopoli, Sastry & Lee, CDC, 1999)

Dynamic Networks of Hybrid Automata

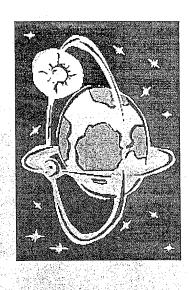
Omola

Continuous Time and Discrete Event Dynamical Systems

- Ptolemy II

Hierarchical Heterogeneous System with Multiple Model of Computations (MOC)

- Hierarchical Hybrid System Simulation(Liu, Liu, Koo, Sinopoli, Sastry & Lee, CDC, 1999)
  - Modeling of Hybrid System
- Finite State Machine
- Continuous Time Dynamics
- -- Mixed-Mode Simulation in Ptolemyll
- ু Event Detection/Genërator
- ODE Solver
- · Jinvariant Monitor



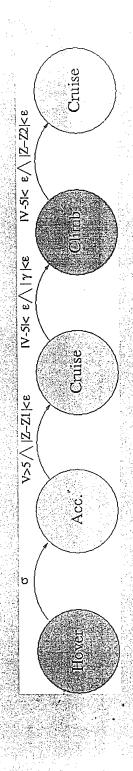
- Hierarchical Hybrid System Simulation(Liu, Liu, Koo, Sinopoli, Sastry & Lee, CDC, 1999)
- Modeling of complex flight mode switching of helicopter in take-off phase
- 2D helicopter model
- Flight mode control design based on feedback linearization

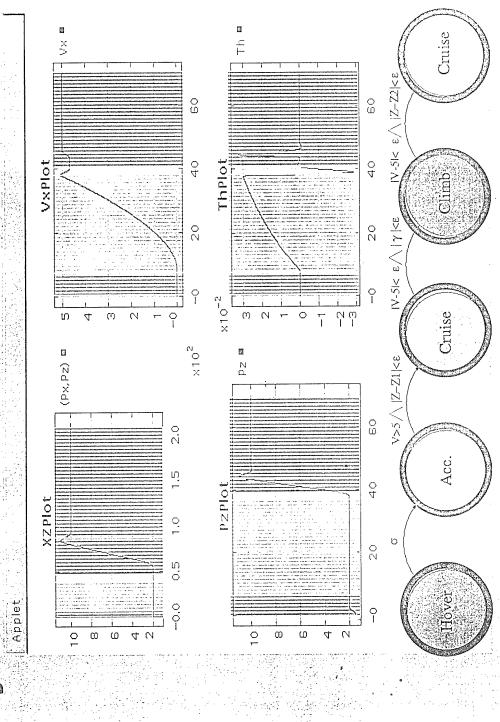
$$\begin{bmatrix} \ddot{p}x \\ \ddot{p}z \end{bmatrix} = \frac{1}{m} R(\theta) \begin{bmatrix} R^T(\alpha) \begin{bmatrix} -D(V) \\ 0 \end{bmatrix} - \begin{bmatrix} T_M \sin \alpha \end{bmatrix} + \begin{bmatrix} 0 \\ g \end{bmatrix},$$
$$\ddot{\theta} = \frac{1}{I_y} (M_M \alpha + h_M T_M \sin \alpha), \quad \alpha = \theta - \tan^{-1} (\frac{\dot{p}z}{\dot{p}x})$$

Ulierarchical Hybrid System Simulation (Liu, Liu, Koo, Sinopoli, Sastry & Lee, CDC, 1999)

- Modeling of complex flight mode switching of Finelicopter in take-off phase

Flight mode automaton





\_\_\_2D Longitudinal Aircraft Dynamics (Lygeros et. al., 1999)\*

$$\dot{V} = \frac{T - D(V, \gamma, \theta)}{m} - g \sin \gamma, \quad \dot{\gamma} = \frac{L(V, \gamma, \theta)}{m} - \frac{g \cos \gamma}{V}$$

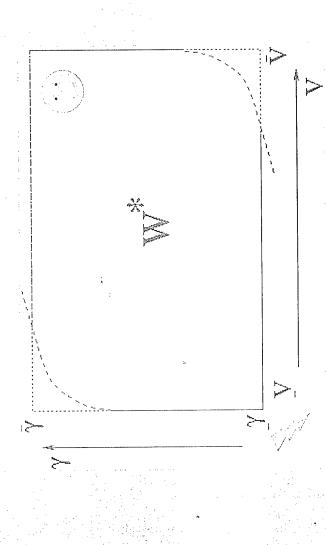
- 2 States and 2 Inputs  $x = [V \ \gamma]^T, \quad u = [T \ heta]^T$ 

$$(x) = 0 \text{ for } i = 1, ..., 4$$

$$- \mbox{ Flight Envelope } \qquad l^i(x) = 0 \mbox{ for } i = 1, \ldots, 4$$
 
$$= \mbox{ Safe Set } \qquad F = \{x \in X \mid \forall i \in \{1, 2, 3, 4\}, \ \ l^i(x) \geq 0\}$$

Envelope Protecting Controller Synthesis

- Determine the largest controlled invariant safe set
  - Classify the least restrictive safe controls



○ Envelope Protecting Controller Synthesis

Function 
$$j^i(x,u(\cdot\,),t)=l^i(x(0))$$

- Value Function 
$$f'(x,u(\cdot\,),t)=l^i(x(0))$$
 - Optimal Cost 
$$f^{i*}(x,t)=\max_{u(\cdot)\in U}f^i(x,u(\cdot\,),t)$$
 - Optimal Hamiltonian

- Optimal Hamiltonian 
$$J^*(x,t) = \max_{u(\cdot) \in U} J^*(x,u(\cdot),t)$$
 - Optimal Hamiltonian 
$$H^{i*}(x,p) = \max_{u \in U} p^T f(x,u)$$
 - Hamilton-Jacobi equation 
$$H^{i*}(x,p) = \max_{u \in U} p^T f(x,u)$$

$$-\frac{\partial J^{i*}(x,t)}{\partial t} = \min\{0, \max_{u(\cdot) \in U} \frac{\partial J^{i*}(x,t)}{\partial x} f(x,u)\}$$
$$J^{i*}(x,0) = l^i(x)$$

Solved by analytical method and simulation (Lygeros et. al.,

# Proposed Numerical Method

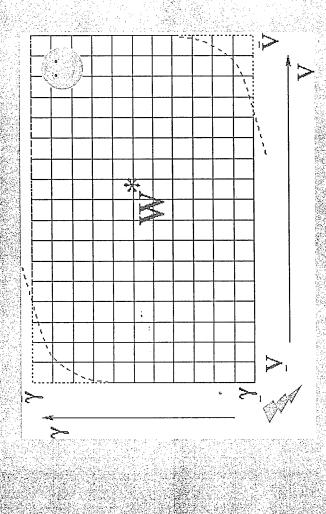
- Based on Finite Element Method
- Value function defined at each node and interpolated in each element
- Game between approximation error and control
- $= \underbrace{\int_{-\infty}^{\infty} f(x,t) = \max_{u(\cdot) \in U} \min_{u(\cdot) \in U} \left[ \widehat{J}^{s}(x,u(\cdot),t) + d(\cdot) \right]}_{u(\cdot) \in U}$  Hamilton-Jacobi equation Optimal cost

$$-\partial \widetilde{J}^{i*}(x,t) = \min\{0, \max_{u \in U} \min_{d \in D} \{\partial \widetilde{J}^{i*}(x,t) f(x,u) + \delta(d)\}\}$$

$$J^{i*}(x,0) = l^{i}(x)$$

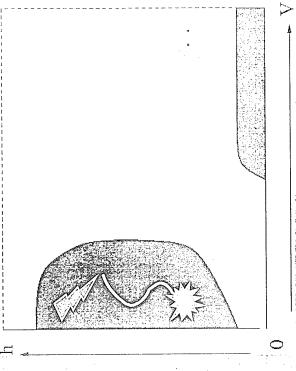
Proposed Numerical Method

— Result will be compared with the analytical one for validation



= Dead Man's Curve, the Height-Velocity diagram Extension to Helicopter Application

If the engine fails while the line helicopter is in the safe area, there exists an autorotation procedure to land safely.



- Extension to Helicopter Application
- Extension to 2D Longitudinal Helicopter Dynamics

$$\begin{bmatrix} \ddot{p}x \\ \ddot{p}z \end{bmatrix} = \frac{1}{m}R(\theta) \begin{bmatrix} R^T(\alpha) \begin{bmatrix} -D(V) \\ 0 \end{bmatrix} - \begin{bmatrix} T_M \sin a \\ T_M \cos a \end{bmatrix} \end{bmatrix} + \begin{bmatrix} 0 \\ g \end{bmatrix},$$
$$\ddot{\theta} = \frac{1}{I_y} \left( M_M \ a + h_M T_M \sin a \right), \quad \alpha = \theta - \tan^{-1} \left( \frac{\dot{p}z}{\dot{p}x} \right)$$

. Eased on Dead Man's Curve, the Height-Velocity diagram, there are 3 States and 2 Inputs

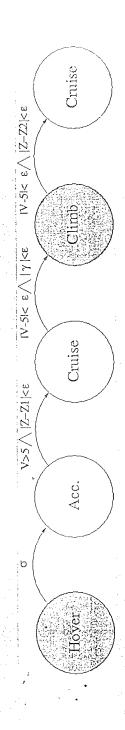
$$x = [\dot{p}_x \ p_z \ \dot{p}_z]^T, \quad u = [T_M \ \theta]^T$$

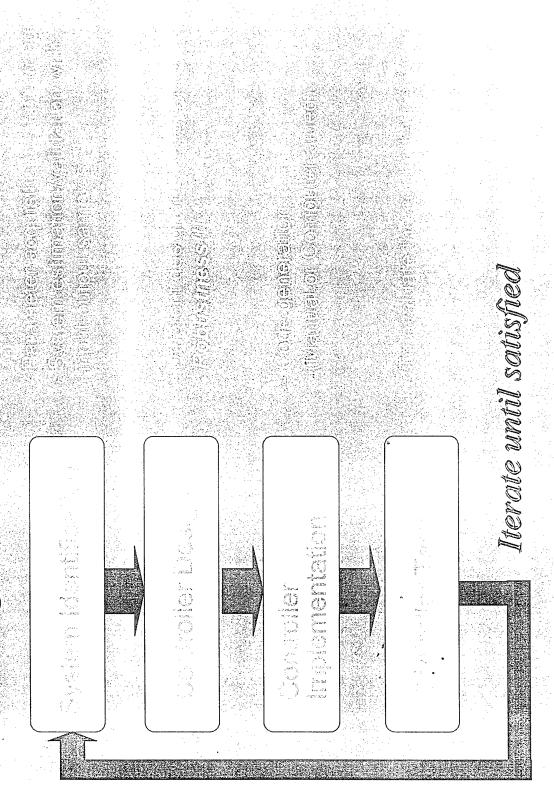
- Apply the same Numerical Method to solve the problem

### Future Research

# ○ Flight Mode Hybrid Automaton Synthesis

- Objective
- Develop an algorithm to construct a flight mode hybrid automaton to satisfy the given specification
- Problem
- Liveness ← Reachability
- Example





System Modeling & Identification

- Spreadsheet-based linear state equation generator (and much more)
- C-based linear state equation generator ancestor to the spread-sheet version
- Parameterized Nonlinear helicopter model analysis tool using Mathematica.
- Matlab CMEX code for Simulink

## Existing Tools- Visualization

Off-line 3D visualization

- Useful tool to visualize the 3D motion of multiple number of UAV's
- Uses OpenGL extension in Windows 98/NT
- DDE (Dynamic Data Exchange) enhanced version

available--frajectory generated by

Mattab or any other software supporting DDE is

directly connected

### Development Environment Towards an Integrated

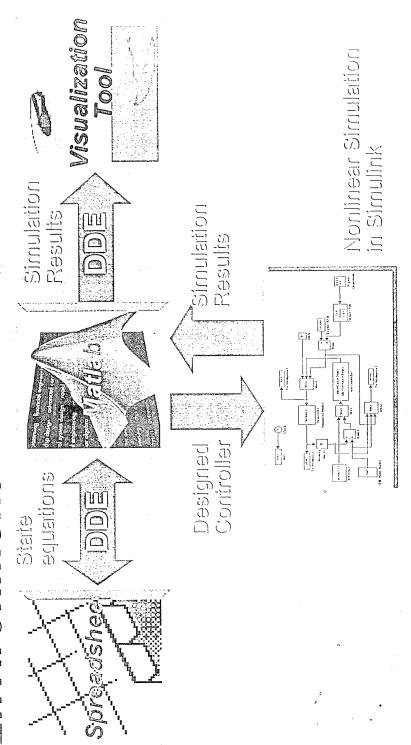
Current situation: Isolated tools

- application software and different OS. - Tools are realized using different
- Information has to be manually
- As the steps are iterated, human errors are likely to be introduced.

### Development Millorant Toyalds An Integrated

Toolntegration

- Provide the "link" among the software
- interfaces for rapid prototyping - Design convenient, intuitive user
- semi-automatic tools are available
- Realtine workshop, D-space, Matrix-X



### Faculdade de Engenharia da Universidade do Porto Departamento de Engenharia Química Instituto de Sistemas e Robótica

### Issues on computer-aided process operation: Hybrid networks for Process Modelling and Control

Sebastião Feyo de Azevedo and Rui Oliveira

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Workshop on
Future Directions in Systems and Control Theory

22-25 June, 1999 Hotel Baía, Cascais, Portugal

### Issues on Computer-aided Process Operation: Hybrid Networks for Process Modelling and Control

### Sebastião Feyo de Azevedo and Rui Oliveira

Department of Chemical Engineering / Institute for Systems and Robotics, Faculty of Engineering, University of Porto, Rua dos Bragas, 4099 Porto Codex, Portugal, E-mail: sfeyo@fe.up.pt

Issues concerning the theory and practice of computer-aided process operation (CAPO) will be addressed in this lecture. In essence, the topics to be discussed relate to new emerging knowledge engineering techniques and to how they can be used and integrated in the so-called 'process industries' for improving their performance.

The development of new or improved forms of process operation, be it a chemical or a biochemical process, is only successfully achieved when it is possible to match the theoretical innovation with the technology available for implementation at industrial scale. A kind of landmark in the history of CAPO can be recognised as having been reached at the close of the eighties. Nowadays, a large number of control systems suppliers offer the capabilities of the digital technology, employing open architecture and standard operating systems and, particularly, allowing external and independent modules to be incorporated into the control configurations. The flexibility and computational power are now available, with industrial standards, to implement monitoring and identification strategies, to develop software sensors, to implement, at local level, new and more efficient digital controllers and, at supervisory level, knowledge-based applications. Artificial Neural Networks and Fuzzy Inferential Systems are today tools which can be incorporated into the available industrial equipment without hard computational power constraints.

The phenomenological knowledge available is usually scarce and its use for implementing supervisory strategies is generally difficult and too expensive. For this reason many decisions concerning process operation keep being made today on the basis of the heuristic knowledge of plant engineers and operators. Knowledge engineering techniques open the possibility for incorporating qualitative information and information hidden in process data records into the supervisory system, thus increasing greatly the spectrum of knowledge available for improving process performance.

This lecture will focus on a new technique: Knowledge-Based Hybrid Networks for process monitoring, control and optimisation.. Such Networks are computational structures which combine available classical mathematical models with knowledge-based numeric computation techniques. The advantage of such a methodology in comparison to the classic phenomenological model-based approach alone is that more knowledge can be used: i) the heuristic knowledge of process engineers and operators - using Fuzzy Inference Systems - and ii) the knowledge hidden in process data records - using Neural computational methods.

The concepts will be illustrated with the application to the operation of fermentation processes.

### References

Bastin, G and D. Dochain, On-line Estimation and Adaptive Control of Reactors, Elsevier, Amsterdam, 1990

Schubert, J., R. Simutis, M. Dors, I. Havlik and A. Lübbert, Bioprocess Optimisation and Control: Application of Hybrid Modelling, J. of Biotechnology, 35, 51-68, 1994

Montague, G. and J. Morris, Neural-network contributions in biotechnology, Tibtech, 12 312-323, (August) 1994.

Menezes, J.C., S. Alves, J. Lemos and S. Feyo de Azevedo, Mathematical Modelling of Industrial Pilot-Plant Penicillin-G Fed-Batch Fermentations, J. Chem Tech. Biotechnology, 61 123-138, 1994.

Menezes, J.C., Analysis and Modelling of Penicillin-G production at pilot scale, Ph.D. Thesis, Universidade Técnica de Lisboa, 1996 (in Portuguese).

Oliveira, R., E. Ferreira, F. Oliveira and S. Feyo de Azevedo, A Study on the Convergence of Observer-Based Kinetics Estimators in Stirred Tank Bioreactors, Journal of Process Control, <u>6</u> (6) 367-371, 1996.

Simutis, R. Oliveira, M. Manikowski, S. Feyo de Azevedo and A. Lübbert, How to Increase the Performance of Models for Process Optimization and Control, J. Biotechnology, 59, 73-89, 1997

Feyo de Azevedo, S., B. Dham and F. Oliveira, Hybrid Modelling of Biochemical Processes: a comparison with the conventional approach, Computers Chem. Engng, 21 Suppl., S751-S756, 1997

Oliveira, R., Supervision, Control and Optimisation of Biotechnological Processes, Ph.D. Thesis, Martin-Lutter Universität, Halle-Wittenberg, Germany, 1998

### Plan for the Talk

- ① Scope
- ② Progress in Computer-Aided Process Operation
  - Technology and (vs.) theory
  - Prevailing bottlenecks
- 3 Capturing and representing the knowledge
  - Forms of knowledge and modelling approaches
- Model-based and Hybrid methods for process monitoring and control
- ⑤ Case-studies
  - ☐ Software sensors mechanistic and hybrid approaches
  - ☐ Hybrid modelling and process control
- © Some concluding thoughts
  - The Human factor investment, knowledge and industrial structure

### Progress in computer-aided process operation

### About the (old) gap between theory and practice

The development of new or improved forms of process operation is only successfully achieved when

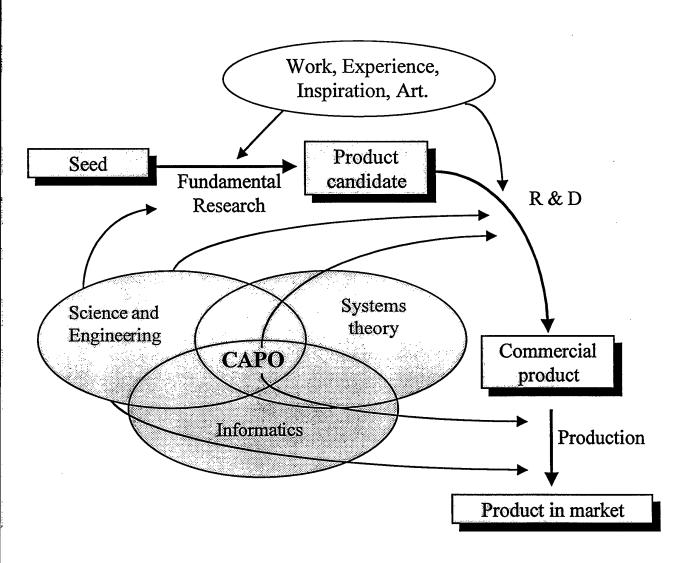


It is possible to match theoretical innovation with the technology available for implementation at industrial scale

Advances in digital technology paved the way for a new area of interest

Computer-Aided Process Operation

### Computer-Aided Process Operation Interdisciplinary View



### Progress in computer-aided process operation I - identification of areas of interest

$\Rightarrow$	Progress in digital technology -			
	0	sensors		
	and			
	0	control systems		
$\Rightarrow$	Progress in theory -			
	0	in process modelling and control		
	or, wider			
	0	in process systems engineering		
 □	Concern with the Human Factor, as a limstep in the pace of development-			
	0	new expertise in the production team		
	0	organizational changes in Companies		

### Progress in computer-aided process operation II - process measurements

- Sensors and analytical instruments are the primary elements for process monitoring
  - O In spite of the observed progress in measurement technology -
    - To a large extent the technological
       bottleneck is in process measurements

### At present -

O indirect measurements are still required for important properties.

### Serving as example, not yet achieved -

O reliable direct measurement of crystal size distribution in industrial crystallisation

or

O measurement of biomass in fermentation processes

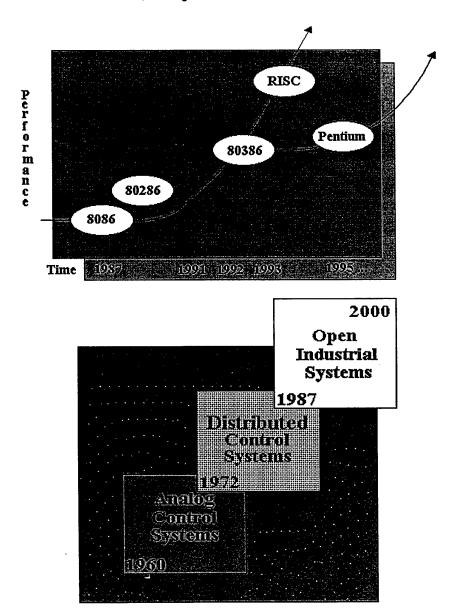
### Progress in computer-aided process operation III - industrial control systems

- A landmark in the history of CAPO has been reached at the close of the eighties
- Nowadays, control systems suppliers offer open architecture, standard operating systems and employ standard communications protocols, allowing -
  - O programming with high level languages

and

O integration of USER-TAILORED applications

### **Evolution in Computer Control Systems and Control Systems Architectures**



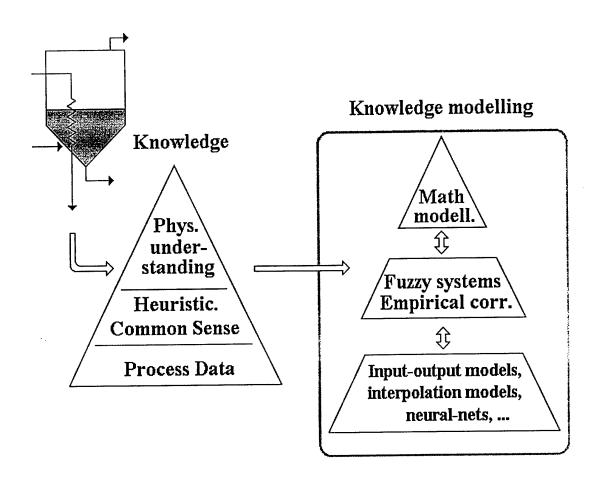
### Progress in computer-aided process operation IV - Towards model-based methodologies

<b>F</b>	Model-based methodologies:		
	0	Re-thinking of concepts on capturing and representing process knowledge	
	O Employing knowledge engineering approache		
	0	Employing hybrid approaches - Combining different forms of knowledge through some (more or less) 'fuzzy' decision	
	٠.	☐ Mechanistic models	
		☐ Empirical models	
		☐ Artificial neural networks	

### Progress in computer-aided process operation V - Process measurement and control

<b>®</b>	Process measurements - Software sensors		
			Mechanistic models
			Artificial neural networks
			Hybrid models
F	Process control		
	0	Sig	nificant progress in conventional control
	0	O Model Based Process Control (MBPC)	
			Model reference adaptive control
			Model based (adaptive)-predictive control
	<ul><li>O Hybrid approaches for process control</li><li>O Real time knowledge based systems (RTKBS)</li></ul>		

### Capturing and representing process knowledge I - forms of knowledge



## Capturing and representing process knowledge II - modelling approaches

Mechanistic (first principles) models

$$\frac{d\xi}{dt} = r(\xi) - D\xi + F - Q(\xi)$$

Input-output (stochastic) models

$$A(q^{-1}) y(t) = B(q^{-1}) u(t) + C(t) \omega(t)$$

where

$$q^{-1} y(t) = y(t-1)$$

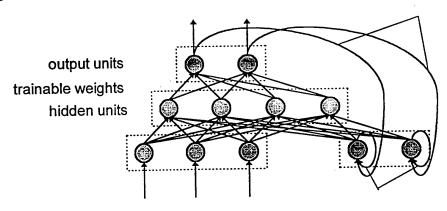
e.g.: Level control (h) with Outlet Flowrate (Q)

$$\hat{h}_k = \sum_{i=1}^2 a_i h_{k-i} + \sum_{j=1}^2 b_j Q_{k-j}$$

# Capturing and representing process knowledge II - modelling approaches (cont.)

#### AI models

eg.: Jordan Neural-Net



- Hybrid models (Mechanistic + ANN and/or Fuzzy and/or RTKBS)
  - O Capturing hidden knowledge and avoiding violation of first principles

A topic in the front line of concern is that of -

#### **Bottleneck - lack of reliable measurements**

- monitoring the behaviour of internal process variables which define the so-called process state and for which direct measurements are either
  - not available,
  - □ difficult,
  - expensive
  - ☐ or inaccurate
- Software sensors a concept to overcome such difficulties

## Software sensors and on-line state estimation I - general

- ① The concept of 'software sensors' is a major development, made possible by computers, towards the objective of full monitoring of process operation.
- ② In general, 'software sensors' should be seen as a method by which with a minimum number of direct measurements we are able to fully describe the process state at any point of operation.

### Software sensors and on-line state estimation II- based on mechanistic models

3	Often 'software sensors' consist only in the
	manipulation of simple algebraic relationships.



That is the case for supersaturation in crystalization processes.

- ④ In other instances, the 'sensor' requires the use of the full deterministic model.
  - ☐ Usually one should look for some form of transformation which eliminates the 'less accurately known' terms in the model.



Invariably these are 'kinetic rate' terms

## Software sensors and on-line state estimation III- based on ANN or Hybrid approaches

⑤ In other cases 'black-box' approaches are employed.



This raises major questions of confidence on results outside training areas

 Hybrid solutions envolving mechanistic models and ANN may represent a good solution for the applied problem



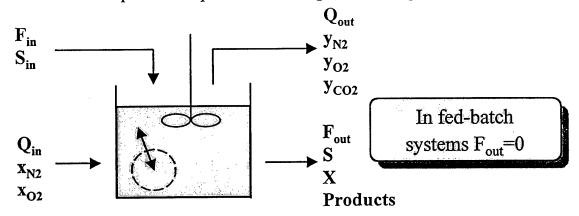
Capturing hidden knowledge and avoiding violation of first principles

#### **Modelling and Control of Fermentation Processes**

<b>F</b>	Cooperation with					
	□	University of Minho, Braga, Portugal				
		Martin-Luther University, Halle-Wittenberg, Germany				
		CESAME, Louvain-la-Neuve, Belgium				
€°	General objectives - modelling and control of biological reactors					
	σ	Major difficulties related with the 'unpredictable' behaviour of biological systems				
	0	Significant difficulties when applying mechanistic models 'only'				
	٥	AI methods for capturing knowledge				
	٥	Looking into hybrid solutions				

### Basic concepts Mechanistic model for fermentation processes

Let us consider a production process involving microbian growth



e.g.: Mass balance to substrate

$$F_{in}S_{in} = F_{out}S + r_SV + SVR + \frac{d(VS)}{dt}$$
 and 
$$\frac{dV}{dt} = F_{in} - F_{out}$$

☐ Expanding and re-arranging

$$\frac{dS}{dt} = -r_s - DS + DS_{in}$$

where

$$D = \frac{F_{in}}{V}$$

Dilution rate

#### Mechanistic model for fermentation processes (cont.)

The case of Baker's yeast production

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and we can write the model

with

OTR = 
$$K_{e_{O2}} a [O*-O]$$
  $O* > O$   
CTR =  $K_{e_{CO2}} a [C*-C]$   $C > C*$ 

OTR and CTR can be estimated on-line from mass balances to the system

# General problem: cell systems are extremely complex!

- ✓ A full mathematical description of cells metabolism (cell level and population level) is too complex
- ✓ Available segregated and structured cell models are at the moment "out of range" for bioprocess optimization
- ✓ Hybrid models:
  - O <u>Disadvantage</u>: Hybrid models are of considerable complexity ⇒ require sophisticated software tools and computation power

#### **General Dynamical Model** for Fermentation Processes

$$\frac{d\xi}{dt} = r(\xi) - D\xi + F - Q(\xi)$$

$$r(\xi) = ?$$

$$r(\xi) = K \varphi(\xi)$$

$$r(\xi) = K H(\xi) \rho(\xi)$$

#### **Advanced Monitoring** Software sensors / State estimation (Bastin & Dochain, 1990)

$$= F - Q$$

$$\frac{d\xi}{dt} = K\varphi(\xi, t) - D\xi + U$$

$$2 \text{ state partitions:}$$

$$\xi_1 \ (\in \mathbb{R}^p) \text{ and } \xi_2 \ (\in \mathbb{R}^{n-p})$$

#### On-line estimation of $\xi_2$ , given:

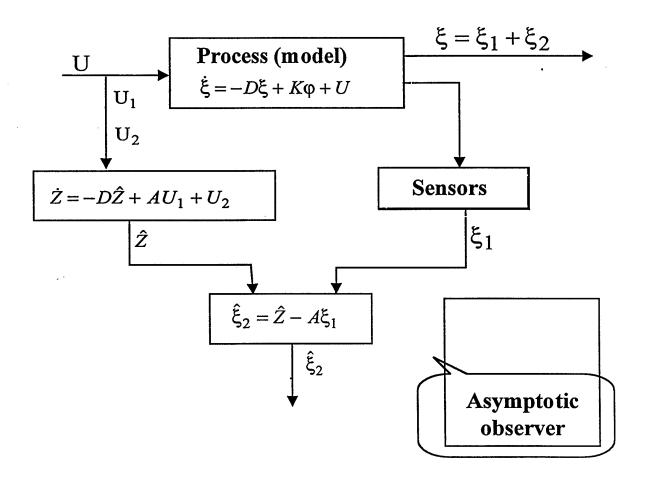
- ✓ φ unknown
  ✓ p measured state variables (ξ₁)
  - ✓ D, U (F, Q) measured on-line
  - ✓ coefficients of K known

$$\frac{d\xi_1}{dt} = K_1 \varphi - D\xi_1 + U_1$$
$$\frac{d\xi_2}{dt} = K_2 \varphi - D\xi_2 + U_2$$

Make: 
$$Z=A\xi_1+\xi_2$$
 where  $AK_1+K_2=0$ 

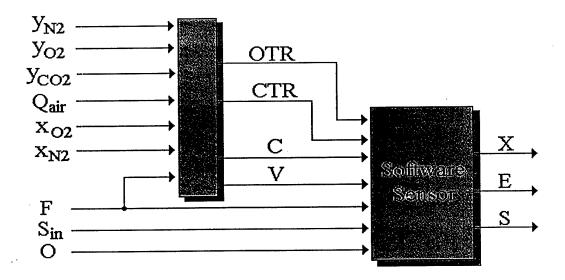
Get: 
$$\frac{dZ}{dt} = -DZ + AU_1 + AU_2$$
Got rid of  $\varphi$  !!!

### Advanced Monitoring Software sensors / State estimation (cont.)



### Model-based state observer for Baker's Yeast fermentation - I

- Estimation of OTR e CTR by mass balances to the gas phase
- Partial kinetics models

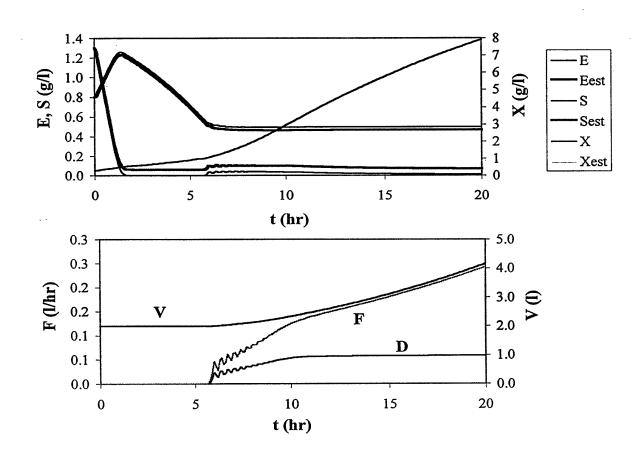


 $\square$  Sampling rate = 6 min

#### State observers and PID control (simulation)

#### Conditions

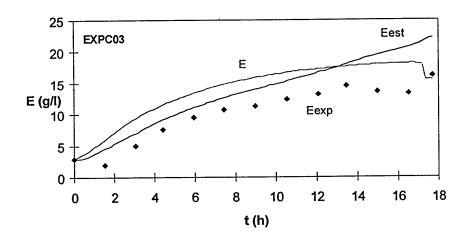
- $E_0=0.8 \text{ g/l}$ ;  $S_0=1.3 \text{ g/l}$ ;  $X_0=0.3 \text{ g/l}$ ;
- $V_0=2 l$ ;  $F_0=0 l/hr$ ; Sin=30 g/l;
- Kc=2.5 (l/hr)/(g/l);  $\tau_I$ =0.5 hr;  $\tau_d$ =0.05 hr

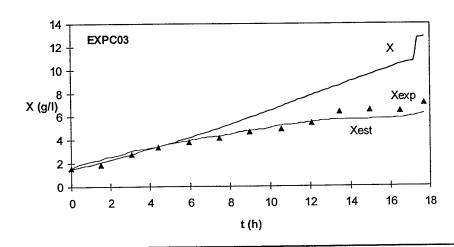


#### Model-based state observers (experimental)

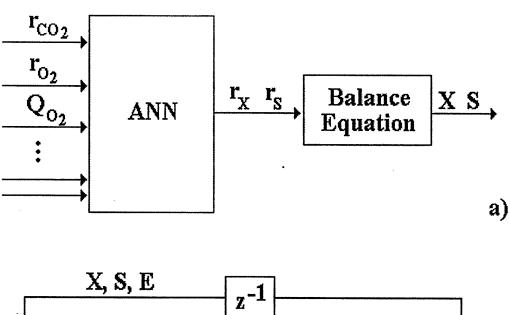
#### • Operating conditions:

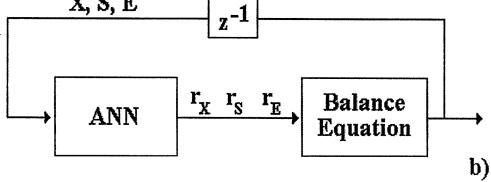
• 
$$S_{in} = 100 \text{ g/l}$$
;  $F = 0.15 \text{ l/hr}$ ;  $V_0 = 2.5 \text{ l}$ 



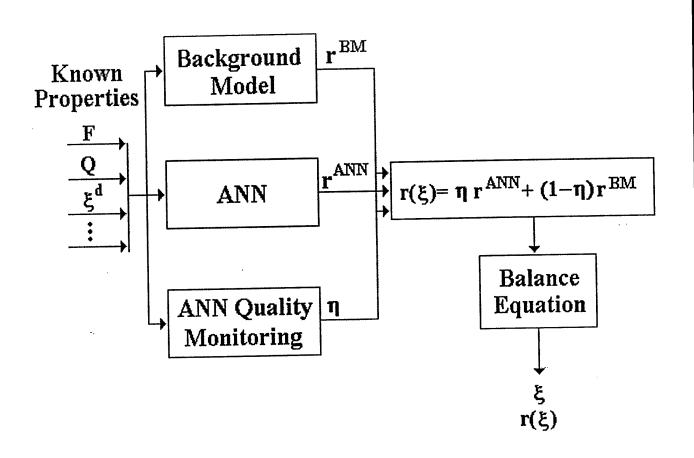


#### Hybrid modelling of fermentation processes - I

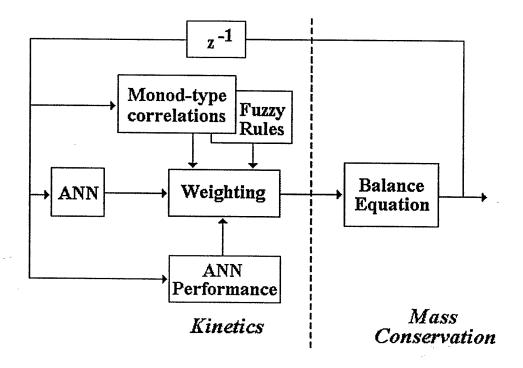




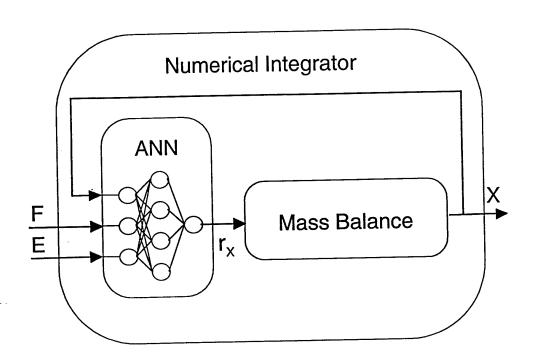
#### Hybrid modelling of fermentation processes - II Monitoring ANN performance



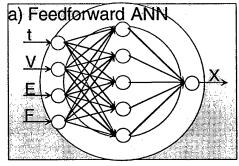
#### **Hybrid modelling of fermentation processes - III**

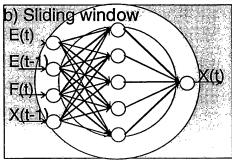


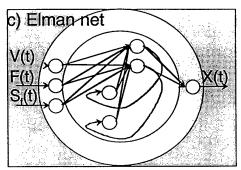
# Hybrid Modelling Case-Study with baker's yeast production I - Structure



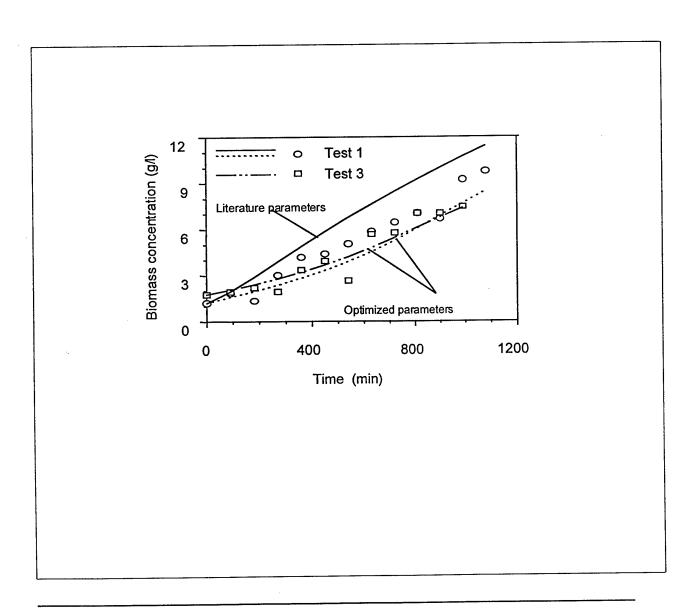
#### Hybrid Modelling Case-Study with baker's yeast production II - Neural-networks employed



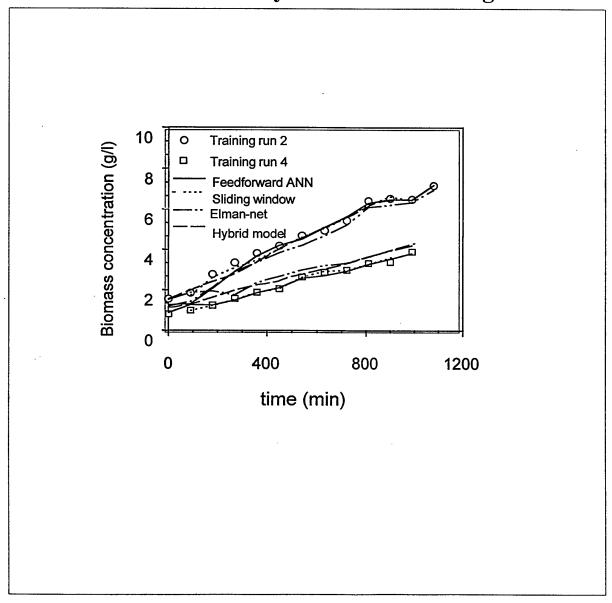




# Hybrid Modelling Case-Study with baker's yeast production III - Predictions with mechanistic model

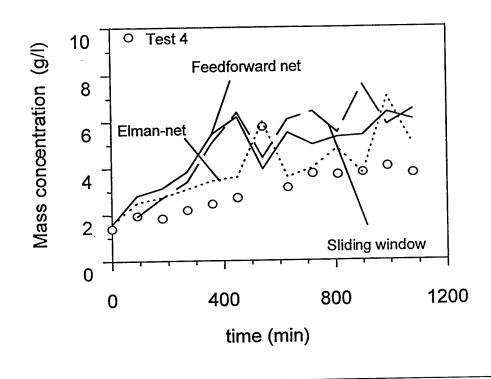


# Hybrid Modelling Case-Study with baker's yeast production IV - ANN and hybrid model training

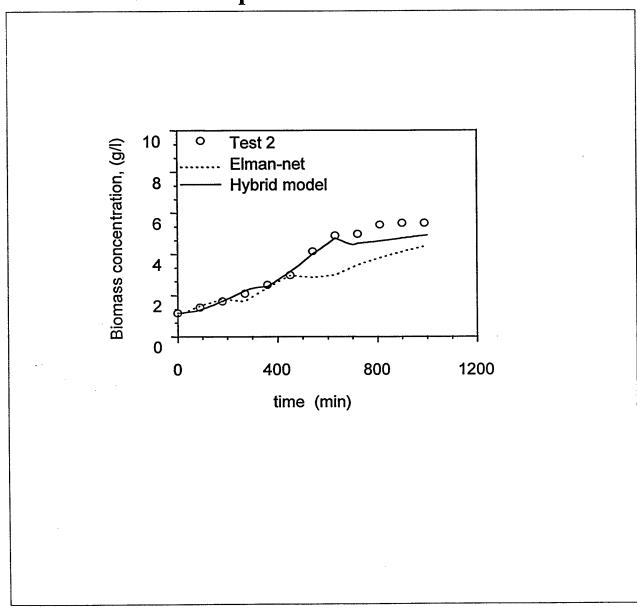


#### **Hybrid Modelling**

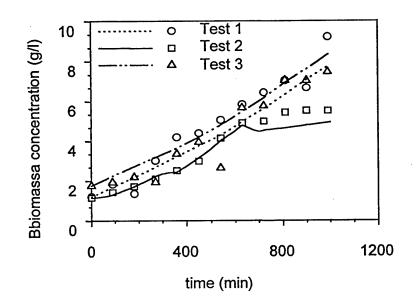
### Case-Study with baker's yeast production V - Pure ANN test



# Hybrid Modelling Case-Study with baker's yeast production VI - Test: pure ANN versus HM



# Hybrid Modelling Case-Study with baker's yeast production VII - Testing of hybrid model



## Case-study: Penicillin production process

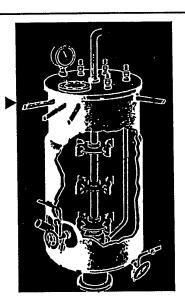
(substrate) + a (precursor) + b 
$$NH_3$$
 + c  $O_2$  =

d (biomass) + e (penicillin) + 
$$f(CO_2)$$
 +  $g(H_2O)$ 

#### ✓ N manipulatable variables

Φ.

- ✓ Power input (Air flow, Agit.)
- Initial medium composition
- ✓ operation:batch, fed-batch, pulse
- Input flow rates of several components
- ✓ Rate of heat removal
- Fermentation time

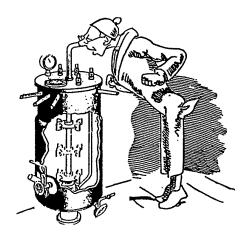


#### Process performance index (J)

- Productivity
- O Product quality

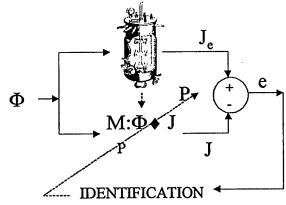
#### Model-based open-loop control

#### Trial-and-error



- o Empirical method: intuition and experience.
- o Good luck is an essential condition to be successful in this way.
- Slow process improvement
- o More experiments

#### Model-based



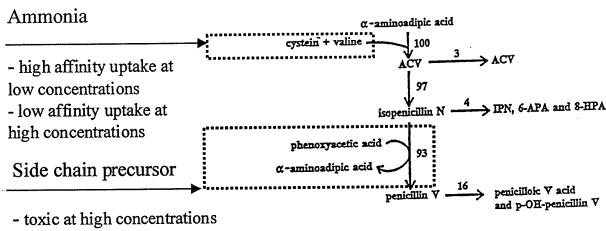
- ✓ Identification:
  - o Model ≡ Process
- ✓ Optimisation:
  - Φ<sub>opt</sub> calculated analytically or numerically

$$max (J(\Phi,P))$$
  $\Phi$ 

# Automatic control of ammonia and side chain precursor concentrations in a penicillin production process

- ✓ The concentrations of ammonia  $(C_N)$  and side chain precursor  $(C_{PA})$  in the broth have a great influence on the penicillin productivity of a given strain.
- ✓ In most industries this control is performed manually by feeding a solution of ammonia  $(F_N)$  and precursor  $(F_{PA})$
- ✓ The measurements of  $C_N$  and  $C_{PA}$  are difficult and expensive. Measurements are made off-line with low frequency.

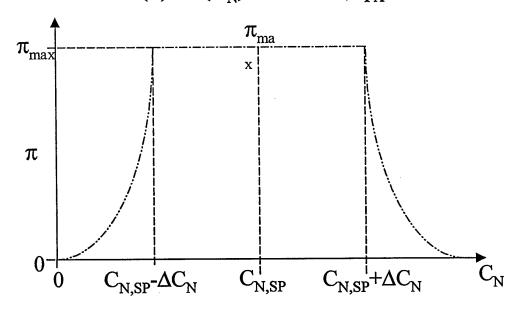
#### Penicillin biosynthesis

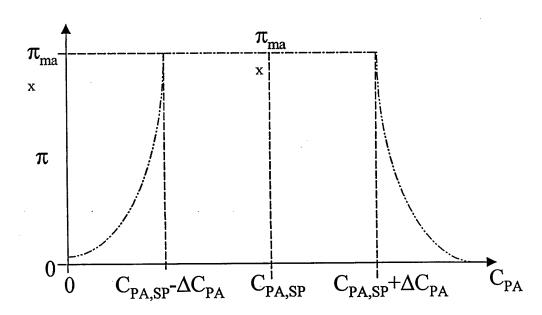


- stimulates the synthesis of penicillin (about 5-fold by penicillin G)

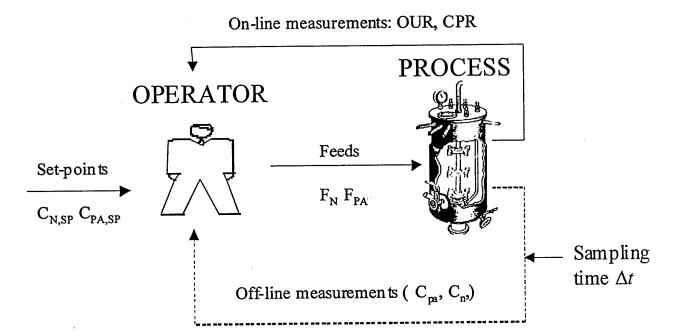
✓ Ammonia and side chain precursor concentrations must be kept constant at optimal values for maximum penicillin productivity!

### Experimental evidence -dependency of specific penicillin production rate ( $\pi$ ) on ( $C_N$ ) and on ( $C_{PA}$ )





#### Manual empirical control



- ✓ Expensive off-line measurements (high  $\Delta t$ )
- ✓ Classical (PID) control not feasible
  - Manual control

## Manual empirical control (12 Fermentations)

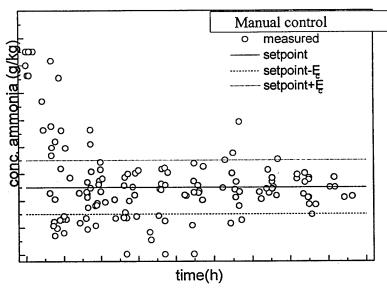


Figure 1. Concentration of ammonia for 12 fermentations controlled manually

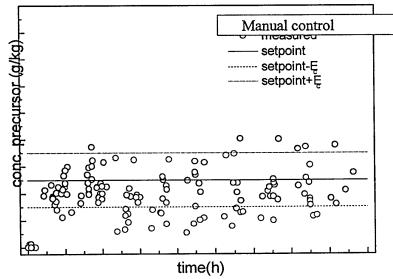
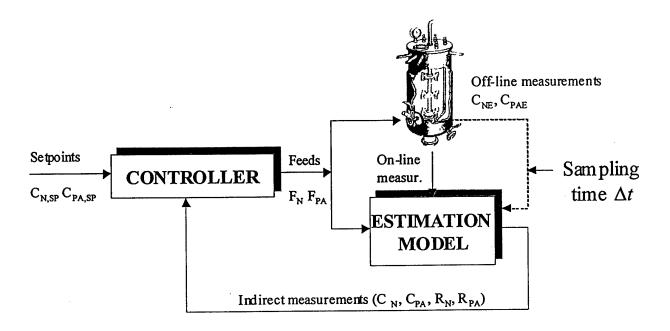


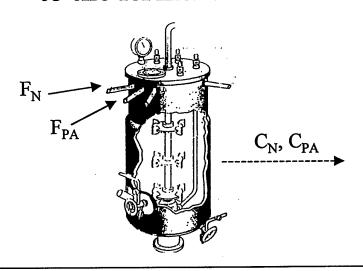
Figure 2. Concentration of precursor for 12 fermentations controlled manually

#### Inferential control system



✓ Estimation (or prediction) model for the concentrations of ammonia and precursor between off-line measurements

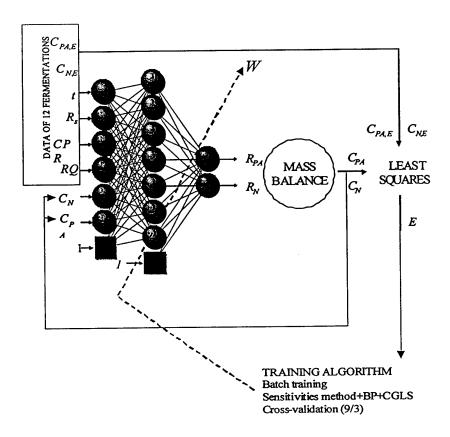
## Macroscopic mass balance to the fermenter



$$\frac{dC_N}{dt} = \begin{bmatrix} -R_N + \frac{F_N}{W}C_{FN} - \frac{F_{tot}}{W}C_N \\ \frac{dC_{PA}}{dt} = \begin{bmatrix} -R_{PA} + \frac{F_{PA}}{W}C_{FPA} - \frac{F_{tot}}{W}C_{PA} \\ \frac{F_{PA}}{W}C_{PA} - \frac{F_{tot}}{W}C_{PA} \end{bmatrix}$$
Accumulation rate | Production rate | Input feed rate | Dilution rate | Production ra

ASSUMPTION: Well-mixed bioreactors KINETIC MODEL = ?

#### **ANN-Kinetic Model**



- ✓ Feedforward ANN {6,7,2}
- √ 65 ANN parameters (dim(W)=65)
- √ 9 Fermentations for training (8137 experimental points)
- ✓ 3 Fermentations for validation (2311 experimental points)

BP - Backpropagation; CGLS - Conjugate Gradients with Line-Search

### Training algorithm

Objective function: minimization of precursor and ammonia estimation errors according to a batch least-squares criterion (P - number of total measured points):

$$E = \left(\frac{1}{P} \sum_{t=1}^{P} ([\alpha(C_{PAE}(t) - C_{PA}(t))]^{2} + [\beta(C_{NE}(t) - C_{N}(t))]^{2}\right)^{\frac{1}{2}}$$

The objective function gradients are obtained by differentiating the previous equation with respect to the ANN parameters vector (W)

$$\frac{\partial E}{\partial W} = -\frac{1}{E P} \sum_{t=1}^{P} \left( \alpha (C_{PAE}(t) - C_{PA}(t)) \frac{\partial C_{PA}(t)}{\partial W} + \beta (C_{NE}(t) - C_{N}(t)) \frac{\partial C_{N}(t)}{\partial W} \right)$$

 $\partial C_{PA}/\partial W$  and  $\partial C_N/\partial W$  is calculated with the sensitivities method

$$\frac{d(\frac{\partial C_N}{\partial W})}{dt} = -(\frac{\partial R_N}{\partial C_N} + \frac{F_{tot}}{W})\frac{\partial C_N}{\partial W} - \frac{\partial R_N}{\partial C_{PA}}\frac{\partial C_{PA}}{\partial W} - \frac{\partial R_N}{\partial W}$$

Initial conditions:  $(\partial C_N/\partial W)_{t=0}=0$  and  $(\partial C_{PA}/\partial W)_{t=0}=0$ 

 $\partial R_N/\partial C_{PA}$  ,  $\partial R_N/\partial C_N$  and  $\partial R_N/\partial W$  are calculated by applying the backpropagation algorithm to the ANN

# Comparison of different kinetic models (mean absolute estimation error) for 12 fermentations

	AMMONIA	PRECURSOR
$R_{PA} = \frac{aM_{PA}}{M_S} R_S = Y_{PA/S} R_S$ $R_N = \frac{17b}{M_S} R_S = Y_{N/S} R_S$ $EXIVATION OF THE PART OF THE$	$1.06~\Delta C_{ m N}$	1.29 ΔC <sub>PA</sub>
$f_c = \frac{R_s}{M_s} - CPR$ $R_N = a_1 f_c + b_1$ $R_{PA} = a_2(t) f_c + b_2(t)$ $R_{PA} = a_2(t) f_c + b_2(t)$	1.09 ΔC <sub>N</sub>	1.19 ΔC <sub>PA</sub>
BLACK-BOX	$0.53~\Delta C_{ m N}$	$0.80~\Delta C_{PA}$

✓ The ANN model gives best results for the 'training data set'

#### Problem:

Neural Networks are unreliable in extrapolation conditions!

#### Measuring the reliability of the ANN Kinetics: Clustering

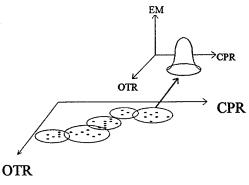
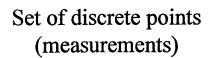
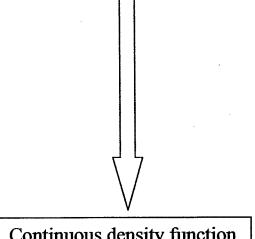


Fig. 1 - Clustering a set of points in a 2-dimensional data space  $D = \{X_1, X_2, ...\}$ 





Continuous density function (extrapolation measure - EM)

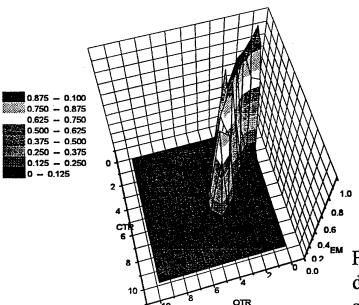


Fig. 2 - Continuous Probability distribution in a 2-dimensional space (Clusters-representation)

### Clustering concept - I

 $\checkmark N$  measured input vectors:

$${X_{t}} = {x_{1}, x_{2}, ..., x_{N}} \subset {X}$$

✓ M clusters (multivariate gaussian distributions):

$$(M \le N/3),$$

Cluster i, defined by -

 $c_i$  - vector defining the *ith* cluster center

 $\sigma_i$  - standard deviation

For a given work input vector x, define -

$$N_{i}(c_{i},\sigma_{i},x) = e^{-\|x-c_{i}\|^{2}/\sigma_{i}^{2}}$$

✓ Extrapolation measure - EM:

$$EM(x) = max(N_1(x,c_1,\sigma_1),N_2(x,c_2,\sigma_2),...,N_M(x,c_M,\sigma_M))$$

### **Clustering concept - II**

✓ Clustering algorithm: vector  $\underline{\mathbf{c}}$ , for  $x \in \{X_t\}$ :

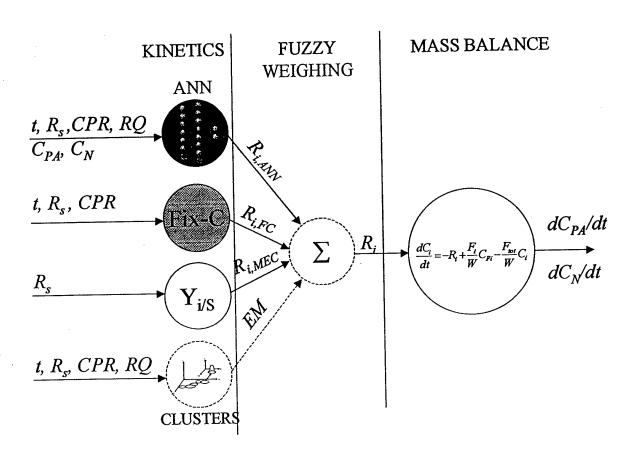
$$E = \sum_{i=1}^{N} \min(||x_i - c_1||, ..., ||x_i - c_C||) \qquad \min_{c_1, c_2, ..., c_C} (E)$$

Algorithm: k-mean or adaptive k-mean (Lloyd (1957), MacQueen (1967))

#### ✓ Standard deviation:

- either uniform and heuristically defined
  suggested 1/10 of range
- o or algorithm *Global First Nearest-Neighbour*

# Hybrid network estimation model



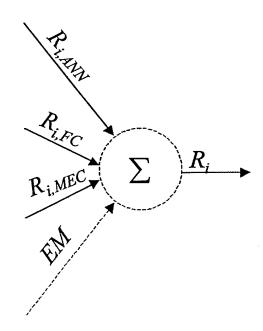
#### Fuzzy weighting node

#### Table II - Fuzzy rules

 $R_1$ : IF (EM is LOW) THEN ( $W_{ANN}$  is LOW and  $W_{FC}$  is LOW and  $W_{MEC}$  is HIGH)

 $R_2$ : IF (EM is MED) THEN ( $W_{ANN}$  is LOW and  $W_{FC}$  is HIGH and  $W_{MEC}$  is LOW)

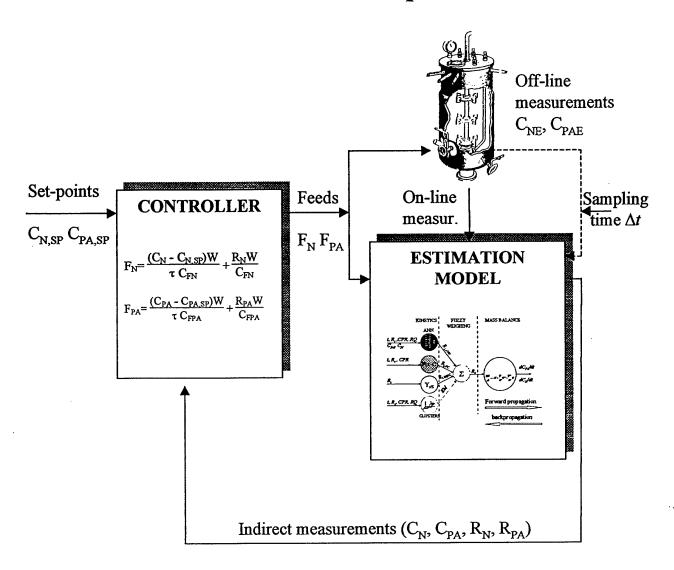
 $R_3$ : IF (EM is HIGH) THEN ( $W_{ANN}$  is HIGH and  $W_{FC}$  is LOW and  $W_{MEC}$  is LOW)



$$R_{N} = \frac{W_{\mathit{ANN}}R_{\mathit{N,ANN}} + W_{\mathit{FC}}R_{\mathit{N,FC}} + W_{\mathit{MEC}}R_{\mathit{N,MEC}}}{W_{\mathit{ANN}} + W_{\mathit{FC}} + W_{\mathit{MEC}}}$$

$$R_{\mathit{PA}} = \frac{W_{\mathit{ANN}} R_{\mathit{PA},\mathit{ANN}} + W_{\mathit{FC}} R_{\mathit{PA},\mathit{FC}} + W_{\mathit{MEC}} R_{\mathit{PA},\mathit{MEC}}}{W_{\mathit{ANN}} + W_{\mathit{FC}} + W_{\mathit{MEC}}}$$

## **Control loop**



# Results: Precursor automatic control 17 new runs in automatic

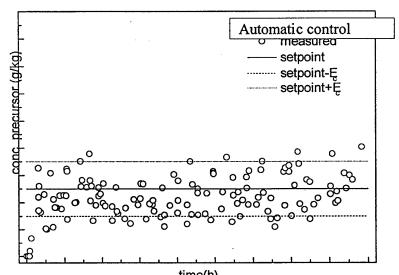


Fig. 1 - Concentration of precursor for 17 fermentations controlled automatically

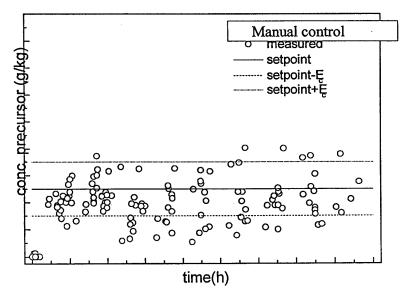


Fig. 2 - Concentration of precursor for 12 fermentations controlled manually (data used to develop the control system)

# Results: ammonia automatic control 17 new runs in automatic

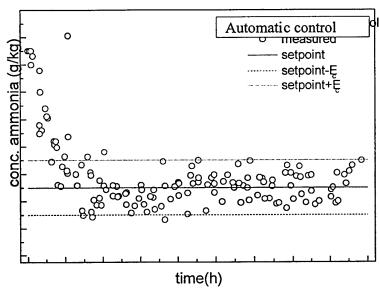


Fig. 3 - Concentration of ammonia for 17 fermentations controlled automatically

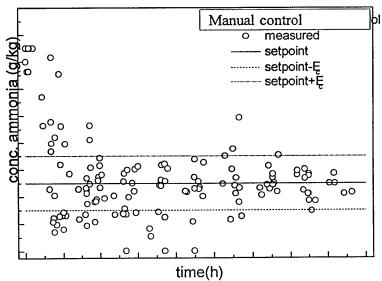


Fig. 4 - Concentration of ammonia for 12 fermentations controlled manually (data used to develop the control system)

#### **Comments about results**

- ✓ Deviations of ammonia concentration:
  - O For automatic operation, the probability of concentration being outside the allowed operating range decreased 18% relatively to manual operation
- ✓ Deviations of precursor concentration:
  - O For automatic operation, the probability of concentration being outside the allowed operating range decreased 22%
- ✓ On-line re-tuning of the hybrid method should be performed

### Some concluding thoughts

- Today, the technological conditions are here, for bringing the theory into practice
- Model-based and adaptive methodologies and AI approaches will play a major role in process operation
- The Human factor as a limiting step in the pace of development
  - O cost investment sometimes difficult to justify in the short-term
  - O lack of human expertise and need of organizational changes in the Companies -
    - ☐ the pneumatic systems engineer of the 50's
    - ☐ the electronics engineer of the 70's,
    - ☐ the digital systems engineer of the 90's,
  - ☐ the process systems engineer of the 00's